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CLASSIFYING HEARTRATE BY CHANGE DETECTION AND WAVELET METHODS FOR EMERGENCY PHYSICIANS *

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Abstract. Heart Rate Variability (HRV) carries a wealth of information about the physiological state and the behaviour of a living subject. Indeed, the heart rate variation is intrinsically linked to the autonomic nervous system: the Parasympathetic and Sympathetic systems. Thus, any imbalance in these two opposite systems results in a variation of the cardiac frequency modulation. It is also recognized that this alternation between equilibrium and disequilibrium (frequency variability) is an indicator of well being and good health. In other words, decreased heart rate variability is always linked to stress, fatigue and decreased physical performances. The aim of this work is to exploit the heart rate signals to detect situations of stress in different populations: emergency physicians, sportsmen, animal behaviours, etc... This paper introduces a methodological framework for the detection of stress and eventually well being. Our contribution is based on first extracting high and low frequencies energies which are linked to the Parasympathetic and Sympathetic systems. We then detect change points on these energies using the Filtered Derivative with p-value (FDpV) method. Finally, we develop a typology of cardiac activity by distinguishing homogeneous groups or state profiles having a characteristic similarity.

We apply our methodology on a real dataset corresponding to an emergency doctor.

Résumé. La variabilité sinusale est porteuse de riches informations sur l'état physiologique et comportemental d'un sujet vivant. En effet, la variation du rythme cardiaque est intrinsèquement liée au système nerveux autonome: les systèmes parasympathique et orthosympathique. Ainsi, tout déséquilibre dans ces deux systèmes se traduit par une variation de la modulation en fréquence cardiaque. Il est également admis que cette alternance entre équilibre et déséquilibre (en l'occurrence ici une grande variabilité de la fréquence) est un indicateur de bonne santé : une diminution de la variabilité sinusale est toujours liée au stress, à la fatigue et au diminution des performances physiques. Le but de ce travail est d'exploiter le rythme cardiaque pour détecter des situations de stress dans différentes populations: medecins urgentistes, sportifs amateurs, comportement d'animaux... Nous élaborons une typologie de l'activité cardiaque en distinguant des groupes homogènes ou des profils d'états ayant une certaine ressemblance.

Nous appliquons ensuite notre méthodologie à un jeu de données réelles correspondant à une garde d'un médecin urgentiste.

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Introduction

Technological development and advanced electronic miniaturisation makes it possible to produce physiological measurement devices which are increasingly reliable and accurate. Indeed, we live on the brink of a massive development of devices and sensors able of doing measurements almost as accurate as in a specialized medical center. For a total autonomy of users, these devices should be handled by the general public without the help of a healthcare professional. The users autonomy will not be insured without the development of novel algorithms and more accurate mathematical models. In this paper we focus on the analysis of RR intervals deduced from the electrocardiogram (ECG) signals which contain a wealth of information on the health status and the internal behaviour of a patient. Indeed ECG signal analysis has a long story after the implementation of the ambulatory monitoring by Holter at the beginning of the fifties. Recent measurement methods, see [8, 10], allow us to record ECG data for healthy people over a long period of time: long distance (marathon) runners, individuals daily (24 hours) records, etc... We then obtain large datasets that allow us to characterise the variations of heartbeat durations in the two components of the nervous autonomous system: the parasympathetic and the orthosympathetic ones.

Until recently, the analysis of these signals was usually made thanks to the experienced eye of cardiologists. Software solutions have recently been introduced and allow some data summary statistics or possibly indications about the physiological state of a user. The most popular is the instantaneous average frequency which is displayed by runners' watches or integrated in some recent smartphones. This quantity gives poor indications about daily activity of a subject and does not summarize all the relevant information. Note that heartbeat data display large variations, clustering, etc, as only individuals with serious diseases display a regular heart rate.

On the other hand, cardiologists are interested in the study of this signal in two frequency bands: the ortho-sympathetic and para-sympathetic bands, i.e., the frequency bands ($0.04\ Hz,\ 0.15Hz$) and ($0.15\ Hz,\ 0.5Hz$) respectively. The definition of these bands is the outcome research work, see e.g., Task force of the European Society of Cardiology and the North American Society Pacing and Electrophysiology [7], and is based on the fact that the energy contained inside these bands would be a relevant indicator on the level of stress of an individual. Indeed, for the heart rate, the parasympathetic system is often compared to the brake while the ortho-sympathetic system would be a nice accelerator; see e.g. [12]. At rest there is a permanent braking effect on the heart rate. Any solicitation of the cardiovascular system, any activity initially produces a reduction of para-sympathetic brake followed by a gradual involvement of the sympathetic system. These mechanisms are very interesting to investigate, especially in the field of physiology. Such data are crucial for measuring the level of vigilance, the level of stress induced by physical activity or level of perceived stress.

Fractal models have been used in cardiology after the works by [13], who applied the multifractal spectrum analysis advocated by [11], for modeling RR series and classifying individuals according to this multifractal spectrum, as this spectrum discriminates between individuals who experienced hearth trouble, and those who did not. However, this tool has some shortcomings as it requires huge samples common in turbulence analysis, and is then inappropriate for studying phenomena occurring at a resolution lower than the daily time interval, such as intra-day variations of parasympathetic and ortho-sympathetic systems.

Wavelet-based methods have been used in biostatistics by [9] for uterine EMG signal analysis. However, they consider that the process studied is homogeneous, and use these methods as a classification tool. Another significant difference is the fact that they use discrete wavelet decomposition, i.e., a frequency decomposition on a dyadic wavelet basis, the choice for the frequency bands is made without reference to a biological phenomenon. In our case, the choice for the frequency band is justified by biological considerations, and we fit the wavelets inside these bands. For these reasons, the continuous analysis of both systems and their quantification is a particularly promising field of research.

In the rest of this paper, our plan will be as follows: In section 1, we describe the probabilistic model and the statistical tools. In Section 2, we process a real dataset corresponding to emergency physicians with these tools. Eventually, Section 3 gives some conclusion and state the direction of future researches.

1. Models and methodological approach

In Subsectin 1.1, we give a brief description of the mathematical model by considering the heart rate activity as a locally stationary process. We present a brief description of the Filtered Derivative with p-Value (FDpV) method enabling the detection of change points. We also detail how we use the Gabor wavelets to extract energies corresponding to the sympathetic and the parasympathetic systems; i.e. the HF and LF bands. Subsection 1.2 contains a description on how we construct the discriminating variables from change points detected on RR-signals, HF and the LF energies. We also present the classification tools used for extracting homogeneous heartrate profiles.

1.1. The RR-signals as a locally stationary process

Even in laboratory conditions, where a precise protocol is followed and the environment is well controlled, heartbeat durations is a random series. Furthermore in real life situation, both environment condition and stress levels vary. In particular, this is the case for emergency physicians, but also for many other cases.

Let us recall that the duration of each heartbeat can be obtained as an RR interval, that is the time interval between two successive R-waves registred by ECG, see Fig.1. Next, we can precisely measure the time of each

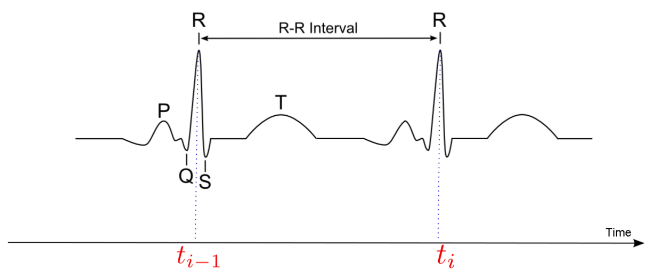

Figure 1. Illustration of RR signal measurment

maximum of R-wave, and we denote it by t_i. Then, the duration of the ith heartbeat is exactly $X_i = t_i - t_{i-1}$. The instantaneous heart rate is provided by the equation $HR = 60/RR$, where $RR = X(t_i)$ is measured in second, HR is measured in beats per minute. For biological reasons, human the heart rate is within the interval $[20, 250]$ *bpm* (beats per minute), i.e., $X(t)$ belongs to the RR interval $60/250s. < X(t) < 60/20s$. In real life situations, it is quite natural to consider nycthemeron activities as a sequence of more or less active periods (sleep, rest, stress,...). This leads to modeling RR-series $X(t_i)$ by locally stationary processes for both time and frequency domains. Therefore, we assume that the signal is the sum of a piecewise constant function and a Gaussian process, centered and locally stationary. We then have the following representation:

$$X(t) = \mu(t) + \int_{\mathbb{R}} e^{it\xi} \sqrt{f(t,\ \xi)} dB(\xi), \quad \text{for all } t \in \mathbb{R}, \tag{1}$$

where

- $B(\xi)$ is a *"well-balanced"* Wiener measure, such that the $X(t)$ is a real number, for all $t \in \mathbb{R}$, see e.g. [17] or [3] [2], for a precise definition.
- The map $\xi \mapsto f(t,\ \xi)$ is an even and positive function, called spectral density. We assume that the spectral density is piecewise constant with respect to time, namely there exists a partition $\tau_1, \ \ldots, \ \tau_K$ such that $f(t, \xi) = f_k(\xi)$ for $t \in [\tau_i, \tau_{i+1}\ [$.
- the function $t \mapsto \mu(t)$ is also piecewise constant for another partition $\tilde{\tau}_1, \ \ldots, \ \tilde{\tau}_L$ with $\mu(t) = \mu_\ell$ if $t \in [\tilde{\tau}_\ell, \tilde{\tau}_{\ell+1}\ [$.

The first step of data processing treated in this work will be the detection of instants where the parameters of the process $X(t)$ will present an abrupt change in either time or frequency components.

Change points detection: the FDpV method

Change points detection is well studied in literature we cite among others: [5, 6]. The classical proposed solutions are usually based on penalized least square techniques which suffer from memory complexity and time consuming calculations. To overcome this problem Bertrand et al. [6] have introduced a faster technique. The main idea of the FDpV method is based on two steps, the first consists in detecting changes without worrying about false detections, the second one consist in performing statistical test to remove false change points. The FDpV method has theoretical complexity of order $\mathcal{O}(n)$ while classical approaches are of order $\mathcal{O}(n^2)$. This technique have been optimized and coded with a java software and is able of making quasi real-time detection.

Time-frequency analysis in HF and LF bands

According to recommendations of Task force [7], we use the following notations :

- $[\omega_1,\ \omega_2] = (0.04Hz,\ 0.15Hz)$ denotes the orthosympathetic frequency band;
- $[\omega_2,\ \omega_3] = (0.15Hz,\ 0.5Hz)$ denotes the parasympathetic band

In order to efficiently extract energies corresponding to HF and LF bands we use techniques presented in [1] or [4]. Indeed they have introduced a theoretical study of the wavelet coefficients for stationary (or with stationary increment) centered Gaussian processes, i.e., for X given by (1) with $\mu(t) = 0$. They have also generalized this result to locally stationary Gaussian processes. We give here a brief description of their technique: Using a suitable wavelets, they extract the energies associated with LF and HF bands and localised around the time b. This is measured by the modulus of the complex wavelet coefficients $|W_i(b)|^2$ for $i = 1, 2$, with

$$W_i(b) \ = \ \int_{\mathbb{R}} \psi_i(\mathrm{t-b}) \ \mathrm{X(t)} \ dt,$$

where ψ_1 and ψ_2 are suitable wavelets chosen with disjoint frequency supports corresponding to the LF and HF bands. These wavelet coefficients are then computed at each second, i.e., the difference between two consecutive values for b is equal to 1 second.

Then we consider the change point problem of the mean of the multivariate time series $Z_1(b)$, $Z_2(b)$ where

$$Z_1(b) = \log\left(|W_1(b)|^2\right), \qquad \text{and} \qquad Z_2(b) = \log\left(|W_2(b)|^2\right), \tag{2}$$

and we use a simple method well suited for big datasets, that is the Filtered Derivative with p-value (FDpV) method [6, 15].

How to choose the wavelets ψ_1 and ψ_2 ?

In the idealistic case, we would use two filters ψ_1 and ψ_2 with compact support, the Fourier transforms of which have support inside the ortho-sympathetic and para-sympathetic bands. Unfortunately, there is no function ψ with compact time domain support and compact frequency support, see for instance [16, Th 2.6 p.34] . Therefore, the best we can do is to choose between a filter with a compact frequency support and a filter with a compact time domain support. The first choice is well suited for stationary models, see [2]. The price to pay for the compactness of the time domain support is the loss in the compactness of the frequency support. To evaluate the effect of the compactness loss, Ayache and Bertrand [1] have introduced the notion of ρ pseudo support. This means that ρ evaluate the energy loss if we force the time support to be compact[1] by evaluating the ratio of energy. The idea is then to adjust the pseudo support inside a specified frequency band where ρ is close to 1. In [3], we have proposed a generic method permitting to find such supports by scaling and modulation. For the sake of readability, let us recall the following proposition:

Proposition 1.1. *Let ψ be a filter with compact support $[L_1,\ L_2]$ and a frequency ρ pseudo support $[\Lambda_1,\ \Lambda_2]$. Let us consider an arbitrary frequency band $[\omega_1, \omega_2]$ and denote,*

[1] *Let* $0 < \rho < 1$, a map $g \in L^2(\mathbb{R})$ and I compact interval. The map g have a ρ pseudo support if $\dfrac{\int_I |g(t)|^2 dt}{\int_{\mathbb{R}} |g(t)|^2 dt} = \rho$.

$$\lambda = \frac{\omega_2 - \omega_1}{\Lambda_2 - \Lambda_1}, \qquad \eta = \frac{\omega_1 + \omega_2}{2} - (\omega_2 - \omega_1)\frac{\Lambda_2 + \Lambda_1}{\Lambda_2 - \Lambda_1}.$$

Then the map $\psi_1(t) = \mu \times e^{i\eta t}\psi(\lambda t)$ with $\mu > 0$ has a ρ pseudo support $[\omega_1,\ \omega_2]$ and a time domain support $\left[\frac{\Lambda_2 - \Lambda_1}{\omega_2 - \omega_1}L_1, \frac{\Lambda_2 - \Lambda_1}{\omega_2 - \omega_1}L_2\right]$.

Proof. Since $\hat{\psi}_1(\xi) = \mu \times \hat{\psi}(\frac{\xi - \eta}{\lambda})$, one can deduce ρ *pseudo supp* $\psi_1 = \eta + \lambda \times \rho$ *pseudo supp* ψ and then the proposition. □

The different choices for the filters ψ_1 and ψ_2 are enlightened by Prop. 1.1. For computational reasons, we will use the Gabor wavelets[2] defined as

$$\psi(t) = e^{i\eta t}g(t) \qquad \text{where} \qquad g(t) = \frac{1}{(\sigma^2\pi)^{1/4}}e^{-\frac{t^2}{2\sigma^2}} \tag{3}$$

see for instance, [16]. This wavelet has the same time and frequency ρ pseudo support $[-L,\ L] = [-3.5, 3.5]$ with $\rho = 0.9995$. In the spectral domain, we have

$$\hat{\psi}(t) = \hat{g}(\xi - \eta),\ \hat{g}(\xi) = (4\pi\sigma^2)^{1/4}e^{\frac{-\sigma^2\xi^2}{2}} \tag{4}$$

By using Prop. 1.1, we can fit the Gabor wavelet inside the ortho-sympathetic band, respectively the para-sympathetic frequency one. We obtain the two Gabor wavelets defined by (3) with the following choice of parameters:

$$\eta_1 = \frac{\omega_1 + \omega_2}{2} \qquad \text{and} \qquad \sigma_1 = \frac{2L}{\omega_2 - \omega_1} \tag{5}$$

$$\eta_2 = \frac{\omega_2 + \omega_3}{2} \qquad \text{and} \qquad \sigma_2 = \frac{2L}{\omega_3 - \omega_2} \tag{6}$$

Moreover $|\rho$ **pseudo Supp** $\psi_1| = \frac{4L^2}{\omega_2 - \omega_1}$ and $|\rho$ **pseudo Supp** $\psi_2| = \frac{4L^2}{\omega_3 - \omega_2}$ with $\rho = 0.9995$. Fig. 3 displays the Gabor wavelets coefficients in the ortho-sympathetic and para-sympathetic bands respectively for the sample plotted in Fig.4.

1.2. Classification and extraction of homogeneous HR profiles

Cluster analysis has been widely studied and used in many applied areas such as medicine, chemistry, social studies and psychology. Its main purpose is to identify groups or clusters present in the data. Clustering algorithms can be divided into two main categories: hierarchical methods and partitioning methods. Hierarchical methods are stepwise and either agglomerative or divisive. Given n objects to be clustered. In each step, two clusters are chosen and merged. This process continues until all objects are clustered into one group. On the other hand, divisive methods begin by putting all objects in one cluster. In each step, a cluster is chosen and split up into two. This process continues until n clusters are produced. While hierarchical methods have been successfully applied to many biological applications (e.g. for producing taxonomies of animals and plants [14]), they are well known to suffer from the fact that they can not undo what was decided previously.

Principal component analysis (PCA) is a powerful tool for analyzing the correlations between several variables. It provides new uncorrelated components with higher informative power; combining the PCA with a hierarchical cluster analysis will overcome the evident strong correlation between the studied variables.

[2] In [3] Daubechies wavelets have been investigated, they give similar results but consume more computation time. Using the Gabor wavelet is more efficient and is at least 8 times faster.

Let us denote $\Theta^R = (\theta_1^R < \theta_2^R < \cdots < \theta_m^R)$, $\Theta^L = (\theta_1^L < \theta_2^L < \cdots < \theta_n^L)$ and $\Theta^H = (\theta_1^H < \theta_2^H < \cdots < \theta_p^H)$ the change points of respectively the RR series, the LF and HF energies. We gather these change points sequences in $\mathcal{T} = \Theta^R \cup \Theta^L \cup \Theta^H$. Let us consider the ordered instants $\mathcal{T} = \tau_1 < \tau_2 < \cdots < \tau_M$ of $\mathcal{T}$ where $M \leq m+n+p$. We will be interested in the following variables:

- The variable $\theta_i^R - \theta_{i-1}^R$ which represents the time laps where the RR signal has a stationary behaviour.
- The variable $\theta_i^H - \theta_{i-1}^H$ which represents the duration of the ith level of the HF energy. This duration can be seen as the duration where only the parasympathetique (braking) system is activated and has fixed regime.
- The variable $\theta_i^L - \theta_{i-1}^L$ which represent the duration of the ith level of the LF energy. This duration can be seen as the laps of time where only the sympathetic (acceleration) system is in action and has established a fixed regime.
- the variable $\tau_i - \tau_{i-1}$ which represents the inter RR, HF and LF durations of the ith level of the HF energy before one of the two systems switches to another state.

For a given subject we will construct a table that describes different states of the heart rate variability during the measurements. In this case we will have M states, for each we have the durations, $\Delta\theta^R$, $\Delta\theta^H$, $\Delta\theta^L$ and $\Delta\tau$. On this laps of time there is at least one change of the heart rate behaviour. This can be represented by the following table:

States	$\Delta\theta^R$	$\Delta\theta^L$	$\Delta\theta^H$	$\Delta\tau$	RR	LF	HF
1	$\theta_2^R - \theta_1^R$	$\theta_2^L - \theta_1^L$	$\theta_2^H - \theta_1^H$	$\tau_2 - \tau_1$	RR_1	LF_1	HF_1
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
M-1	$\theta_M^R - \theta_{M-1}^R$	$\theta_M^L - \theta_{M-1}^L$	$\theta_M^H - \theta_{M-1}^H$	$\tau_M - \tau_{M-1}$	RR_{M-1}	LF_{M-1}	HF_{M-1}
M	$T - \theta_M^R$	$T - \theta_M^L$	$T - \theta_{M-1}^H$	$T - \tau_M$	RR_M	LF_M	HF_M

Table 1: Presentation of the variables used for PCA projection and clustering.

In order to illustrate how the discriminating variables will be constructed we give a simple example in Fig.2.

2. Real case analysis

In this section we apply classification techniques to a real case by investigating heart rate variability of an emergency doctor during 24 hours at the Clermont-Ferrand hospital. Among workers, emergency physicians represent a population at risk because their work consists in management of life threatening emergencies, lack of sleep and fatigue. It is a job demanding long working hours, sustained vigilance and unpredicted stressful situations. In this paper we want to classify different states of HR activity during a work day. For this purpose we make a blind separation of groups that highlights nycthemeral cardiac behaviour. Though we dispose of larger data set with ECG measurements, we will only focus on one subject to show the efficiency of our approach. A further discriminant analysis will be investigated for the whole data collected from the 19 emergency doctor measurements. a is to give a framework to then classify the cohort of emergency physicians.

2.1. Data description

This paper present a methodological approach and can be seen as an introductory work for further study that will concern large number of subjects. Indeed, we dispose of a huge dataset collected from the emergency service of the University Hospital of Clermont-Ferrand, France. The data that we have concerns 19 physicians where

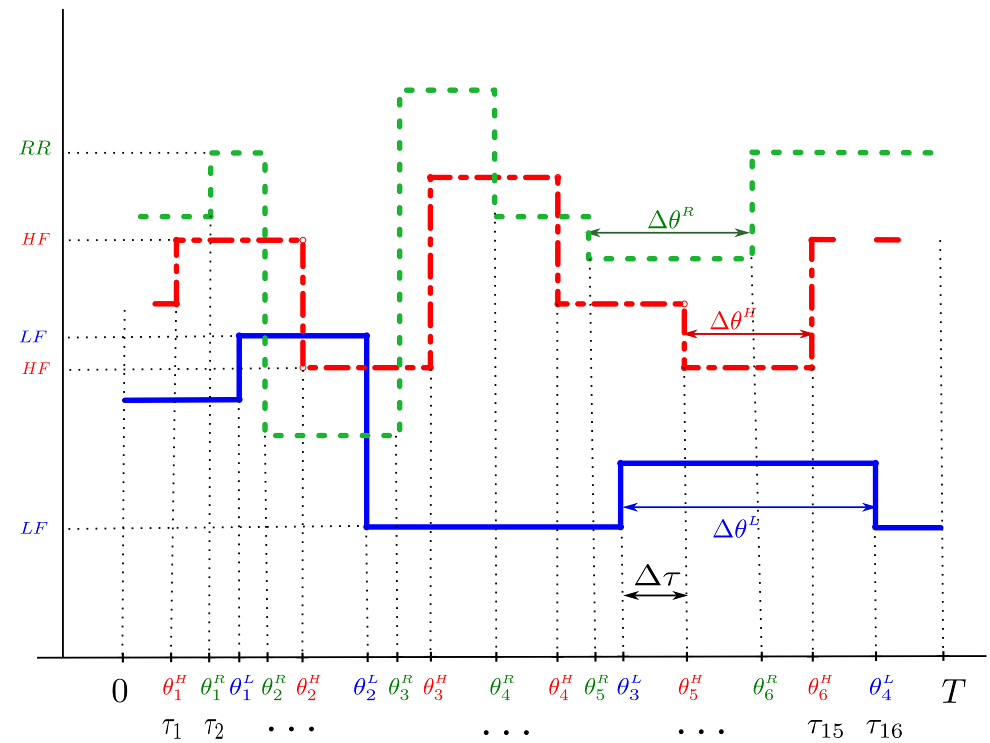

FIGURE 2. Illustration on how we construct the variables $\Delta\tau, \Delta\theta$

exclusion criteria were endocrine disease, pregnancy, deleterious life event, any current illness, anti-inflammatory or chronotropic drugs...etc. The ECG signal analysis was investigated on 24 hours electrocardiogram recorded from 8h30 until 8h30 the next morning; more details about the protocol and data collection can be found in [10]. For technical testing of our approach, we will only use one subject for which the ECG signal has been cleaned by removing the Holter artifact measures and converted to RR signal. The data preprocessing is summarised in the following algorithm:

Algorithm 1: Data preprocessing for the construction of table1

Input: Cleaned RR signal $X(t)$ on time interval $[0, T]$

Find b_0 and b_f first and last possible instant for which wavelets transform can be calculated.

foreach $b = b_0 \dots b_f$ **do**

- Calculate the log-energies $Z_1(b)$ and $Z_2(b)$ given in (2) by using Gabor wavelets ψ_1 and ψ_2.

- Apply the FDpV method on the RR cleaned signal $X(t)$ to extract (θ_i^R) and the corresponding (RR_i)
- Apply the FDpV method to $(Z_1(b), b = b_0...b_f)$ and extract (θ_i^L) and its (LF_i)
- Apply the FDpV method to $(Z_1(b), b = b_0...b_f)$ to extract (θ_i^H) and the corresponding (HF_i)

Deduce the differences $\Delta\theta^R$, $\Delta\theta^L$, $\Delta\theta^H$

Output: Variables $\Delta\theta^R$, $\Delta\theta^L$, $\Delta\theta^H$, mean RR, LF and HF

The output of the last algorithm creates the table 1, in which we consider the columns as the discriminating variables of the heart activity states.

2.2. **Results and graphical representations**

From first glance, we can realize that variables, given in table 1, are correlated and should be reduced to a lower dimension. For this reason we will perform the classification on the principal components instead of the initial data. The idea is to get ride of dependence or correlation between the initial variables and benefit from their orthogonality. After the PCA has been performed we make a hierarchical classification on the resulting principal components. Fig. 3 highlights three distinct clusters reflecting the heart rate behaviour of the subject.

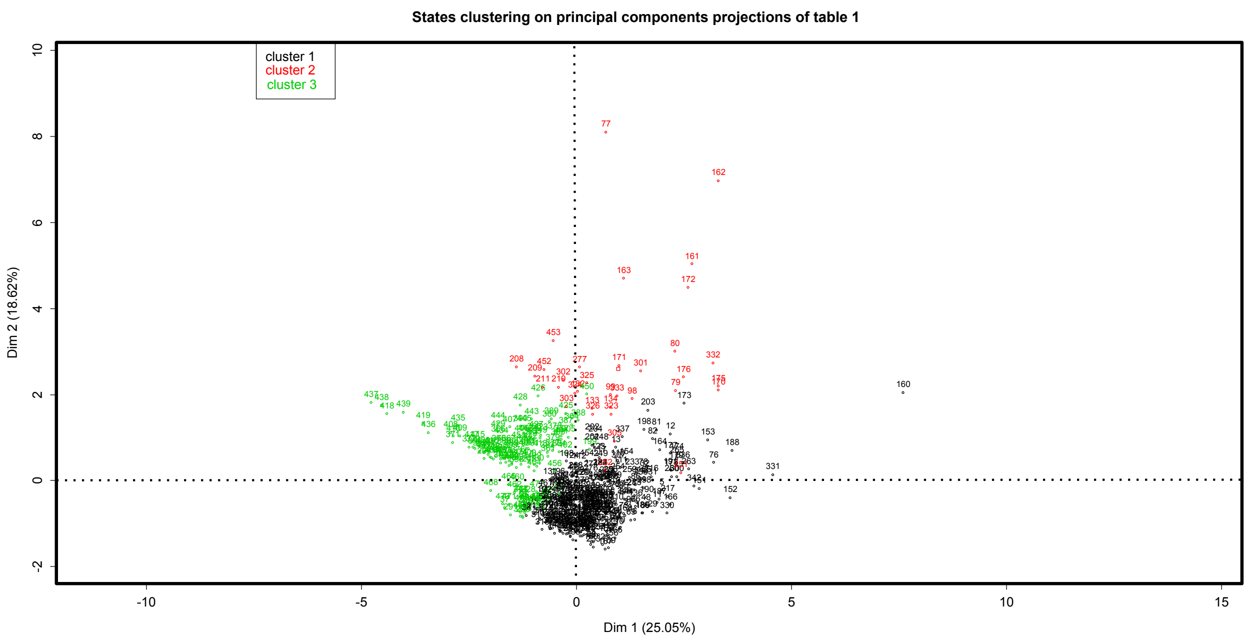

Figure 3. Example of the state projections on the first principal components plan

In order to locate each cluster in the RR, HF and LF during the activity day timeline, we reproduce the mean signals and their corresponding change points. In Fig. 4, we see clearly what happens to the autonomous nervous system activity. We can also quantify the discriminating power of each variable on the classification. Doing so, we determine what characteristics explain most cluster differentiations.

3. Conclusions

We have introduced a methodological approach allowing to highlight the action of the autonomic nervous system on the heart rate activity during the work of an emergency doctor. The use of spectral analysis with Gabor wavelets permits to extract energies corresponding to HF and LF bands. The latter have been used to construct discriminating variables about the way heart rates is modulated by the subject activity.

Further research should be conducted on a large number of subjects. The classification results will be combined with a survey on real feel of subjects during their work. This will allow to extract stress or well being indicators.

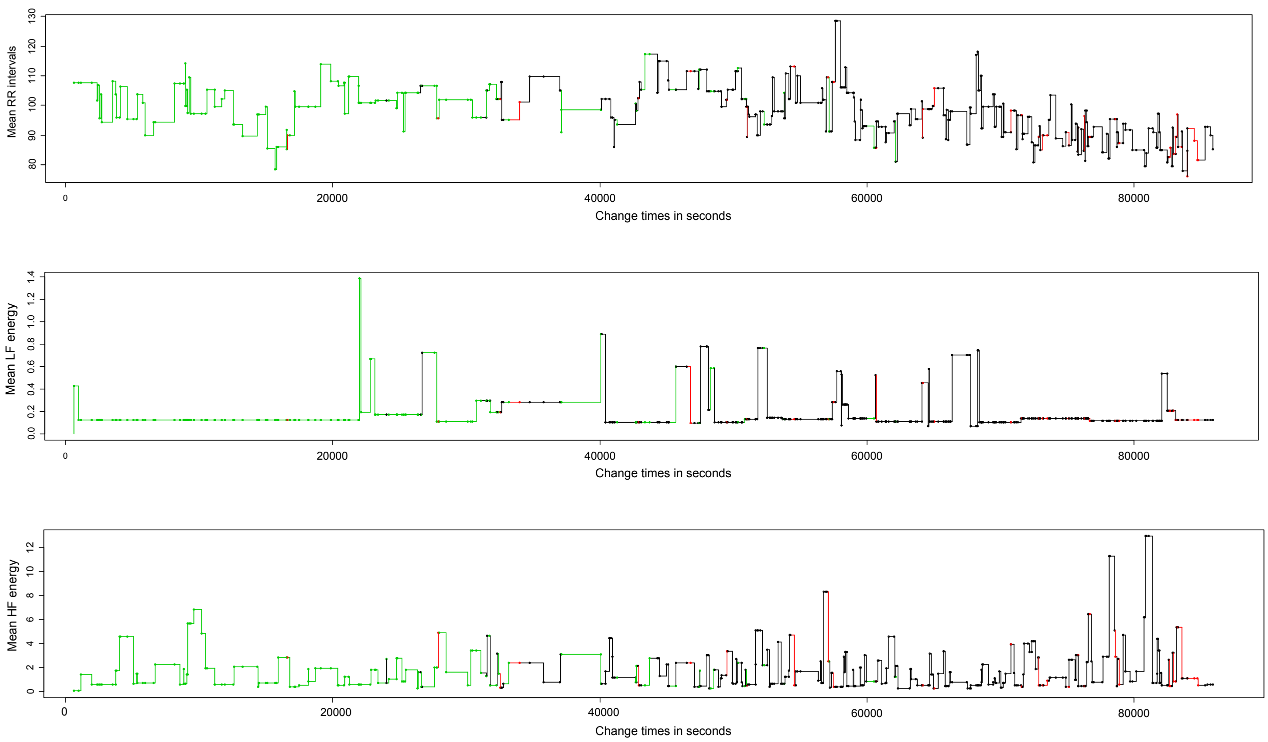

Figure 4. Example of states classification during a 24 hours of work

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